

EXHIBIT E

Quantifying the Economic Risk of Wildfires and Power Lines in San Diego County

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May 2014

Master's project submitted in partial fulfillment of the requirements for the Master of Environmental Management and Master of Forestry degrees in the Nicholas School of the Environment of Duke University
2014

Abstract

San Diego Gas & Electric Company has proposed retrofits to seven of its transmission lines to reduce the lines' potential for igniting fires and to increase their ability to withstand damage from wildfires. Since the company's ratepayers will ultimately pay for the cost of these retrofits through electricity rates, the benefit of the projects in terms of wildfire risk reduction is a matter of public policy interest. This study estimates the range of potential monetary losses that the company could incur due to wildfires and compares those losses to the costs of the transmission line retrofits as a means of evaluating their risk reduction benefit. The study uses a Monte Carlo simulation to estimate the losses for the company from wildfires in a given year. The model outputs the number of ignitions from the transmission lines, the acreage of the resulting wildfires, the property damage caused by those fires, the length of transmission line damaged by wildfires, and the costs of repairing those lines. The model is parameterized using empirical observations of transmission lines ignitions, wildfire sizes, and property values for San Diego County. Results suggest that although the expected value of losses is not large enough to justify the investment in the retrofits, the high risk of losses (driven by rare but extremely damaging events) may justify the investment. The transmission lines in closest proximity to populated areas are the best candidates for retrofits. The study provides a possible framework for regulators and electric utilities to discuss the public benefit of safety-related infrastructure investments as part of the regulatory process.

1.0 Introduction

Electric power infrastructure is vulnerable to disruption and damage from natural hazards, and disasters that strike electricity infrastructure can imperil public safety. High-profile events such as the catastrophic failure of the Fukushima Daiichi nuclear power plant following an earthquake and tsunami and widespread electrical outages in the northeastern United States following Hurricane Sandy have focused attention on the vulnerabilities of the electricity system and their consequences for both the public and utility companies. Disasters such as these are often followed by calls to strengthen the electricity system to withstand hazards and protect public safety. Efforts to increase the resiliency of electricity infrastructure can often entail significant costs, which can increase the price of energy paid by consumers. Policymakers responsible for approving resiliency measures must therefore balance the potential damages of a disaster against the costs of protection. For this reason, it is important to quantify the risks that natural hazards pose to energy infrastructure and compare those risks to the costs of resiliency measures.

This study looks at wildfires in San Diego County as a case study for evaluating the benefits of strengthening electricity infrastructure against natural hazards. This case was chosen because of the unique relationship between electricity infrastructure and the nature of the wildfire hazard: transmission lines have both ignited major fires and been destroyed by wildfires. Following major wildfires in 2007, the local electric utility, San Diego Gas & Electric Company (SDG&E), has undertaken multiple initiatives to reduce its exposure to wildfire risk. One of these initiatives involves fire-hardening transmission lines in high fire risk areas to reduce the potential for ignitions from the lines. This study evaluates the potential fire risks for the transmission lines proposed for fire-hardening retrofits and compares those risks to the costs of the retrofits to evaluate the net benefit to the company.

2.0 Background

The climate and ecology of San Diego County create a landscape that is prone to frequent, intense wildfires. The County has a dry, semi-arid climate characterized by mild winters and hot, dry summers, with most precipitation falling between October and April (Sugihara, van Wagtendonk, Shaffer, Fites-Kaufman, & Thode, 2006). High summer temperatures and low summer precipitation contribute to wildfire risk by drying out available fuels (Sugihara et al, 2006). The County also experiences seasonal outbreaks of hot, powerful winds known as the Santa Ana winds that flow downslope from the interior deserts to the coasts (Sugihara et al, 2006). These winds often result in multiple outbreaks of highly destructive, fast-moving wildfires. Finally, periodic droughts exacerbate these existing conditions by causing vegetation die-back that contributes to a dry fuel load ready to burn (Keeley, 2009). The major vegetative cover types in the County support and in some cases depend upon periodic wildfires. Major fire-prone plant communities in the region include coastal sage scrub, chaparral, oak woodlands, and desert scrub (Minnich, 1988). Chaparral, consisting of woody evergreen shrubs 1-5 meters in height, is notoriously fire-prone (Minnich, 1988).

The wildfire regime of San Diego's natural ecosystems becomes a hazard when humans build in those wildfire-prone landscapes. Increasing human settlement in the wildland-urban interface, "the area where human developments meet or intermingle with undeveloped wildland," increases the potential for the wildfire hazard to become disasters that affect people and property (Grossi, 2008). San Diego County has experienced several major wildfire disasters over the past five decades, reflecting the growing amount of human development in the wildland-urban interface. Three of the twenty most destructive wildfires in California state history, measured by number of structures burned, occurred in San Diego County: the Cedar Fire of October 2003 (273,246 acres

burned, 2,820 structures destroyed, 15 deaths); the Witch Fire of October 2007 (197,990 acres burned, 1,650 structures destroyed, 2 deaths); and the Laguna Fire of September 1970 (175,425 acres burned, 382 structures destroyed, 5 deaths) (California Department of Forestry and Fire Prevention, 2011). Development in the wildland-urban interface is expected to escalate in the future, increasing the exposure of human life and property to wildfire hazard (Grossi, 2008).

One critical component of human development is the provision of utility service, specifically natural gas and electricity. In the San Diego area, the local electricity and gas utility is San Diego Gas & Electric Company (SDG&E), an investor-owned utility that serves 3.4 million customers in a service territory covering 4,100 square miles of San Diego County and southern Orange County (San Diego Gas & Electric Co, November 13, 2007). That service territory includes significant areas of wildfire-prone landscape. SDG&E's obligation to serve customers in the wildland-urban interface requires the company to extend power lines through high fire risk areas (San Diego Gas & Electric Company; Southern California Gas Company, January 5, 2012). As a result, the company incurs the risk of damage from wildfire and the risk of significant financial costs in the case that the company's infrastructure ignites a fire.

In October 2007, the local climate, human settlement of the wildland-urban interface, and SDG&E infrastructure interacted to create a devastating wildfire disaster. Low rainfall in the winter of 2006-2007, a mid-winter cold front that killed vegetation, and a dry summer led to a build-up of dead, dry fuels by the fall of 2007 (California Department of Forestry and Fire Protection, Governor's Office of Emergency Services, U.S. Forest Service, 2008). Between October 20 and 23, the County experienced a multi-day Santa Ana wind event with hot, dry winds of 20 to 40 miles per hour and gusts of up to 80 miles per hour (Cal Fire et al, 2008). The gusting winds damaged several transmission lines owned by SDG&E, leading to the ignition of three fires:

1. The **Witch Fire** was ignited on October 21 on SDG&E Tie Line 637, between the communities of Ramona and San Ysabel (Cal Fire et al, 2008). Two energized conductors on the 69-kV tie line made contact in the high winds (CPUC Consumer Protection & Safety Division, November 12, 2008). The resulting sparks ignited dry vegetation underneath the line, and the high winds caused the fire to quickly grow in size (California Department of Forestry and Fire Prevention, 2008). It eventually burned 197,990 acres, destroyed 1,624 structures, and led to 2 deaths (Cal Fire et al, 2008).
2. The **Guejito Fire** was ignited on October 22 in the San Pasqual Valley (Cal Fire et al, 2008). A lashing wire for a communications cable, co-located on SDG&E utility poles, made contact with an energized 12-kV conductor during high winds (CPUC CPSD, 2008). The fire eventually merged with the Witch Fire.
3. The **Rice Fire** was ignited on October 22 in northern San Diego County when a sycamore tree limb fell onto a SDG&E 12-kV conductor during high winds (CPUC CPSD, 2008). The fire eventually burned 9,472 acres and destroyed 248 structures (Cal Fire et al, 2008).

Firefighters had to contend with five additional fires in San Diego County during the same time period, further straining their resources (Cal Fire et al, 2008). In total, the 2007 fire siege in San Diego required the efforts of more than 6,200 firefighters, 100 aircraft, \$41 million in firefighting expenditures, and 18 days to bring under control (County of San Diego, 2008). Evacuation orders were issued for over half a million residents in San Diego County alone (County of San Diego, 2008). Total economic damages from the San Diego County fires exceeded \$1.5

billion (County of San Diego, 2008). SDG&E estimates that its total legal costs related to the fires will exceed \$2.4 billion (San Diego Gas & Electric Co., 2013).¹

In the aftermath of the 2007 wildfires, SDG&E initiated a suite of programs and projects to reduce its exposure to risk of both financial liability and infrastructure damages from wildfires. One of the most visible of these is a series of investments in the company's 69-kV transmission and 12-kV distribution lines to reduce the likelihood of the equipment igniting a fire and to reduce the potential damage resulting from wildfires (San Diego Gas & Electric Co., July 3, 2013). These projects, referred to as fire-hardening, replace wooden utility poles with steel poles, install heavier conductors, and make associated substation upgrades (SDG&E, 2013). Steel poles are generally stronger and thus better able to withstand extreme wind gusts associated with high fire risk Santa Ana wind conditions (SDG&E, 2013). Stronger steel poles can support a wider spacing of conductors, which, when combined with heavier conductors, lowers the likelihood of high winds causing contact between conductors that could result in line faults, sparking, and potential ignitions of ground vegetation (SDG&E, 2013). The installed steel poles are taller than the wooden poles they replace, so conductors are raised higher above potential ground fires which have the potential to damage line insulation or cause excessive line sag (SDG&E, 2013). Finally, steel poles are more resistant to damage from ground fires than wooden poles.

SDG&E has proposed to undertake a set of fire-hardening projects on 69-kV lines located in areas of its service territory identified as having a high fire risk (SDG&E, 2013). The total cost of these projects approaches \$500 million, and SDG&E has indicated that it will recover the costs of the projects through its rates charged to retail customers and in FERC-authorized electric transmission rates (San Diego Gas & Electric Company, 2012) (San Diego Gas & Electric Company, 2013). However, the public Applications to Construct filed with the California Public Utilities Commission (CPUC) lack information on the value of these projects in reducing wildfire risk (San Diego Gas & Electric Company, 2012). The applications contain a total cost for each project and a narrative description of the benefits, but they do not attempt to quantify the reduction in risk exposure that the company hopes to achieve through the projects. Since SDG&E uses public safety to justify the investments, and since the rate-paying public will ultimately pay for the project through their electric rates, the public should be provided with some estimation of the risk-reduction benefit of the projects.

Table 1. List of proposed SDG&E 69-kV fire hardening projects. Information comes from the Applications to Construct filed with the CPUC.

Project	Location	Length (miles)	Construction cost (millions)	Source
TL 637	Ramona	14.0	\$30 - \$50	SDG&E A.13-03-003
TL 6931	Boulevard	5.2	\$34	SDG&E A.12-12-007
TL 625	Cleveland N.F.	22.5	\$91.7 \pm 5%	SDG&E A.12-10-009
TL 626	Cleveland N.F.	18.8	\$68.7 \pm 5%	SDG&E A.12-10-009
TL 629	Cleveland N.F.	29.8	\$145.8 \pm 5%	SDG&E A.12-10-009
TL 682	Cleveland N.F.	20.2	\$66.3 \pm 5%	SDG&E A.12-10-009
TL 6923	Cleveland N.F.	13.4	\$46.0 \pm 5%	SDG&E A.12-10-009

¹ Although SDG&E has settled hundreds of lawsuits related to the 2007 fires, it has not admitted liability for the fires in the settlement agreements (Jones & Lee, 2012). Similarly, the company has not admitted wrongdoing in its settlements with the CPUC regarding the role of its equipment in the fires.

3.0 Research Question

The goal of this analysis is to quantify the corporate benefit to SDG&E of seven fire-hardening projects by estimating the potential for these projects to reduce wildfire risk. Wildfire risk can be estimated from the probability of SDG&E equipment igniting a wildfire and the monetary damage to structures and property that result from wildfires. The analysis will define risks in terms of the monetary value of wildfire damage to human-built structures and will not consider the social costs of human health impacts or impacts on ecosystems from wildfires. This definition of risk in purely monetary terms is justified for the purposes of this analysis, which seeks to understand the investment decisions of a loss-minimizing corporate entity. The company's legal costs following the 2007 fires have included settlements related to public health and ecosystem damage (Jones J. H., 2013). For example, the City of San Diego sued SDG&E to recover damages related to emergency response expenses and ecological damage; the City and SDG&E later settled for \$27 million (Jones & Lee, 2012). However, the breakdown of SDG&E's settlement expenses by category (property damage, human health impacts, lost revenue, ecosystem damage, etc.) is not public information. For this reason the analysis considers risk only in terms of monetary damage to property because property values are publically available through the San Diego County Tax Assessor.

The analysis will examine two related questions regarding the potential risk reduction from SDG&E's fire-hardening projects:

1. What is the range of potential losses due to wildfires that the company could experience?
2. What is the optimal level of wildfire protection for SDG&E to purchase?

The answers to these questions can help policymakers and the general public make informed decisions about SDG&E's investments.

4.0 Approach

We characterize wildfire risk and the effectiveness of potential protection strategies using a probabilistic analysis informed by historical data. The financial risk resulting from liability² and damages is characterized with the probability distribution of losses that SDG&E would experience in a given year due to wildfires on the seven tie lines that are candidates for retrofits. The benefits of the potential risk-mitigation strategies are characterized through a fire cost minimization curve that compares the cost of each fire-hardening project to the reduction in expected losses resulting from the project. The probability distribution of losses is estimated through a Monte Carlo Simulation model that uses information on past wildfire events to estimate a range of damages for future wildfires.

4.1 Monte Carlo Analysis

A Monte Carlo simulation was created to estimate the probability distribution of potential losses from wildfires for a given year. From this probability distribution, the expected value and variance of annual wildfire losses can be estimated and compared to the costs of fire-hardening strategies. Figure 1 summarizes the Monte Carlo Model. Yellow circles represent random variables with probability distributions taken from historical data and geospatial analysis, as explained in section 5. Orange rectangles represent calculated costs for one iteration of the Monte Carlo simulation, based on independent random draws from each of the random variables.

² The term "liability" is used in this study not in its strict legal sense, but rather as a shorthand for the settlement costs SDG&E might bear should its equipment ignite fires. As discussed above, SDG&E has not admitted liability for the 2007 fires in its legal settlements.

The red rectangles represent the probability distribution of costs resulting from 10,000 iterations of the Monte Carlo simulation. The model is used for each of seven transmission lines, and the expected total losses are evaluated for each line and for the system as a whole.

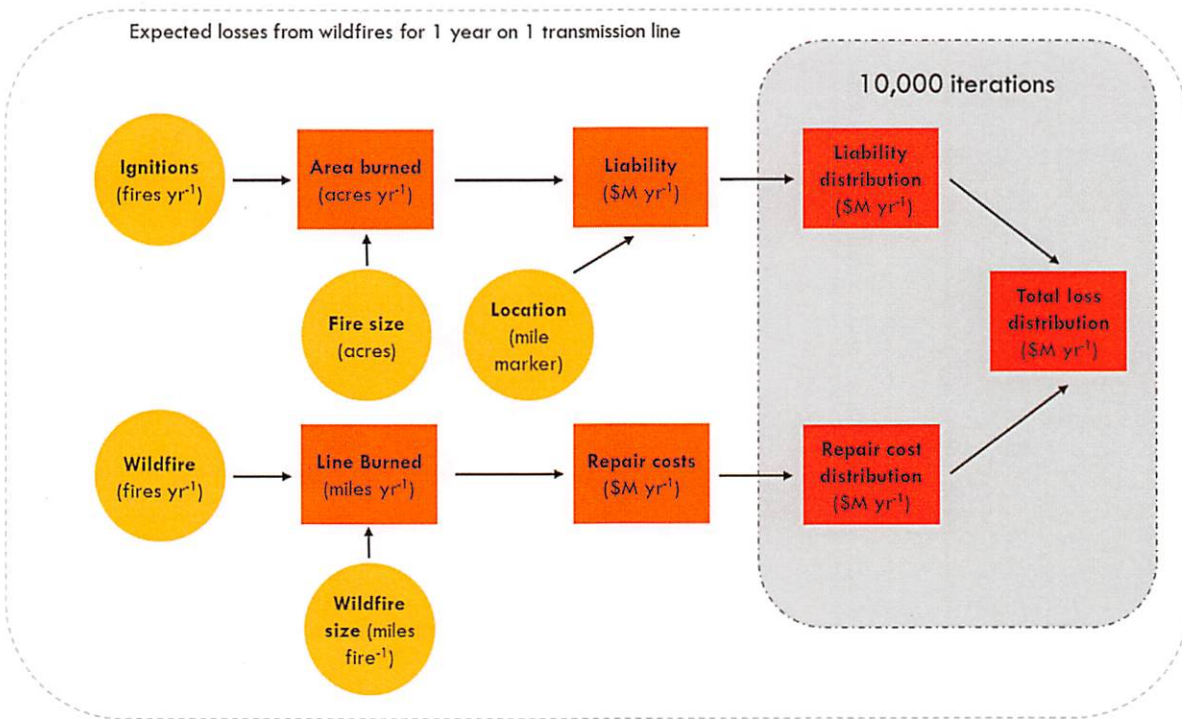


Figure 1. Monte Carlo model schematic. Yellow circles represent random variables; orange rectangles represent outputs for one iteration; red rectangles represent outputs over 10,000 iterations. The simulation is repeated for seven transmission lines. Each iteration represents the wildfire-related losses for a single year.

Total losses are the sum of liability costs and repair costs. The fire-related loss incurred by SDG&E on a given line in a given year is the sum of liability for fires ignited by that line and the costs of repairing that line from wildfire damage. Total losses for the company are found by summing the losses across all seven transmission lines. Total losses are given by:

$$Loss = \sum_{i=1}^7 [Liability_i + Replacement_i] \quad (\text{eq. 1})$$

where: *Loss* = total financial costs incurred by SDG&E in a given year, in dollars.

Liability = SDG&E liability for damage from fires caused by transmission lines, in dollars.

Repair = cost of replacing transmission lines damaged by wildfires, in dollars.

i = index of transmission lines considered for fire-hardening retrofits, 1 through 7.

The company's annual liability for fires on a given line is a function of whether a line ignites a fire, the size of the ignited fires, and the location at which the fire starts. Liability is given by:

$$Liability_i = F(Ignition_i, Fire\ Size_i, Location_i) \quad (\text{eq. 2})$$

where: *Ignition_i* = random variable representing whether or not an ignition occurs on line *i*. It follows a Bernoulli distribution (i.e. takes the values of either 0 or 1), as explained in section 5.1.1.

Fire size_i = random variable representing the area burned by a fire ignited by line *i*, in acres. It is assumed to follow an empirical distribution based on historic fire sizes, as explained in section 5.1.2.

Location_i = random variable representing the point along line *i* at which the fire ignites. It is assumed that the location refers to one of a finite set of points along the line spaced at 0.5 kilometer intervals, as explained in section 5.1.3.

To take one random draw of *Liability* for a particular line *i*, we first take a random draw from *Ignition*. Since *Ignition* has a Bernoulli distribution, no acres are burned if there is no ignition on that line (i.e. if *Ignition* takes a value of 0). If *Ignition* takes a value of 1, then a random draw from the *Fire size* distribution for line *i* is taken, along with a random draw for the *Location* random variable. The specific *Location* along the line, combined with information about the *Fire size*, allows the identification of the specific *Area burned* and permits estimating the *Liability* costs that fire event. Liability costs vary from line to line even for fires of the same size, because fires differ in their proximity to densely populated area. The data used to develop the probability distributions for the *Ignition*, *Fire size*, and *Location* random variables is discussed in Section 5.1.

The company's annual repair costs from wildfires on a given line is a function of whether a wildfire damages the line and how much of the line is damaged. Repair costs are given by:

$$Repair_i = Wildfire_i * Wildfire\ size_i * Repair\ rate \quad (eq. 3)$$

where: *Wildfire* = random variable representing whether or not a wildfire affects a given line. It follows a Bernoulli distribution (i.e. takes the values of either 0 or 1), as explained in section 5.1.4.

Wildfire size = random variable representing the length of line damaged by a given wildfire. It is assumed to follow an empirical distribution based on historical wildfires at the location of the lines, as explained in section 5.1.5.

Repair rate = a fixed per-mile repair and replacement cost, estimated to be \$1.92 million per mile of line.

To take one random draw of *Repair* for a particular line *i*, we first take a random draw from the *Wildfire* distribution. Since *Wildfire* has a Bernoulli distribution, no miles of line are burned if no wildfire occurs on that line. If *Wildfire* takes a value of 1, then a random draw from the *Wildfire size* distribution for that line is taken to determine the length of the *Line burned*, in miles. The length of *Line burned* is then multiplied by a flat repair rate to calculate *Repair* costs. This process is repeated for all line segments.

Table 2 below lists the elements of the Monte Carlo simulation. The data used to parameterize specific elements is discussed in more detail in Section 5.1.

Table 2. List of Monte Carlo simulation elements.

Random Variable	Description	Unit
Ignitions	Ignitions caused by power lines in a given year. Follows Bernoulli distribution $\{0,1\}$ for a given line.	Ignitions per year
Fire size	Area burned by a given fire. Drawn from historical fire size distribution. Indexed by cause (transmission line or not).	Acres
Location	Location along a given tie line at which a fire starts. Follows a uniform distribution with equal probability of occurring at each 0.5 km marker	Marker number
Wildfire	Wildfires affecting power lines in a given year. Follows Bernoulli distribution $\{0,1\}$ for a given line.	Wildfires per year
Wildfire size	Length of line burned by a given wildfire, drawn from an empirical probability distribution based on historical wildfires.	Miles
Output	Description	Unit
Area burned	Area burned by fires ignited by transmission line in a year.	Acres
Liability	Liability for burned area in a year.	\$M
Line burned	Length of line burned by wildfires in a year.	Miles
Repair	Cost of repairing and replacing transmission lines damaged by fire in a year.	\$M
Monte Carlo Output	Description	Unit
Expected liability	Expected liability and variance in expected liability for fires caused by transmission lines in a year, over 10,000 runs.	\$M
Expected repair	Expected replacement costs and variance in expected replacement costs for fires in a year, over 10,000 runs.	\$M
Expected total loss	Expected total costs [liability + replacement] and variance in expected total costs for all fires, over 10,000 runs.	\$M

4.2 Fire Cost Minimization Curve

Protection from wildfire damage, whether in the form of firefighting response capabilities, vegetative fuels treatment, or infrastructure hardening, carries obvious financial costs. SDG&E does not have a public mandate for unlimited spending on wildfire protection. For example, burying the seven 69-kV transmission lines underground would probably be more effective in reducing the risk of accidental ignitions than the proposed aboveground fire-hardening projects, but undergrounding would cost 4-5 times as much (based on transmission cost factors from Southern California Edison and published with CAISO). Finding the optimal level of fire protection requires balancing the costs of protection with the potential damage from wildfire.

The classic approach to finding the optimal level of wildfire protection, first described by Sparhawk in 1925, is to minimize the sum of protection costs and wildfire losses. The basic

premise is that increasing expenditures on wildfire protection reduces financial losses due to fires (Sparhawk, 1925). For example, hiring more fire crews and purchasing more equipment will allow firefighters to bring fires under control more quickly, thereby limiting the fires' geographical extent and damage to timber and buildings. At some level of protection, however, the costs of protection exceed the losses that could arise from the wildfire, and purchasing additional protection is not justified. For example, burying a transmission line at a cost of \$10 million to prevent the potential for fire that would cause at most \$1 million in damage over the lifetime of the line is a sub-optimal allocation of fire protection resources.

If the amount of losses after a given retrofit could be known with certainty, then this "cost plus losses" formulation could be applied to the analysis at hand to state that the economically efficient level of wildfire protection is that which minimizes the sum of fire-hardening retrofit costs plus the damages from fires following the retrofits:

$$\min \sum_{i=1}^7 (\text{Retrofit}_i + \text{Reduced loss}_i) \quad (\text{eq. 4})$$

where: *Retrofit* = the present-value cost of fire-hardening transmission line *i*; and

Reduced loss = the present value of losses following a retrofit of line *i* over the project life.

However, the amount of wildfire-related losses that SDG&E may incur after a retrofit is an uncertain variable. Therefore, to account for the impacts that a retrofit has in reducing the company's exposure to risk, we have chosen to compare the retrofit costs with a *Risk-weighted reduced loss* metric that accounts for both the average losses and the variability in losses after a retrofit:

$$\text{Risk weighted reduced loss} = ([1 - \alpha] * E[\text{Loss}]) + (\alpha * \text{Std. Dev. of loss}) \quad (\text{eq. 5})$$

where: *Risk weighted reduced loss* = a measure of the potential losses that could arise from line *i* after a retrofit;

Expected value of loss = expected value of annual total loss for line *i* after a retrofit;

Standard deviation of loss = standard deviation of annual total loss for line *i* after a retrofit; and

α = the risk premium, used to weight expected value of losses and variability in losses.

In this formulation we allow the risk premium α to take a value between 0 and 1. If $\alpha = 0$, the *risk weighted loss* reflects only the average loss. If $\alpha = 1$, the *risk weighted loss* reflects only the *standard deviation of loss* (i.e. the variability in potential losses). At intermediate values of α , risk weighted loss reflects both average losses and variability in losses. The specific risk premium used by decision-makers in the company is not known, so the analysis considers a range of risk premium values to demonstrate the sensitivity of results to the risk premium used. This formulation is a simplistic utility function based on a linear combination of expected value and standard deviation. There are many other functional forms for a utility function that better represent the risk preferences of a company or a regulator charged with protecting public safety. For details, see Christian Gollier's "The Economics of Risk and Time," MIT Press, 2001.

To estimate the expected value and standard deviation of losses after a retrofit, we take the probability distribution of losses generated by the Monte Carlo simulation described above and multiply by a parameter β that represents the effectiveness of a retrofit in reducing wildfire risk. The assumed risk reduction potential β takes a value from 0 to 1. If $\beta = 0$, the retrofit is assumed to have no effect on reducing potential losses over the project lifetime; if $\beta = 1$, the retrofit is

assumed to completely eliminate all potential losses over the project lifetime. Intermediate values of β reflect realistic risk reduction benefits of the retrofits.

$$E[\text{reduced loss}_i] = \beta * E[\text{losses before retrofit}_i] \quad (\text{eq. 6})$$

$$\text{Std. dev. of reduced loss}_i = \beta * \text{Std. dev. of losses before retrofit}_i \quad (\text{eq. 7})$$

where: *Reduced loss* = the present value of losses following a retrofit over the project life; and
 β = assumed risk reduction potential of the retrofit project.

Note that β is applied to financial losses only, not to the physical parameters contributing to losses (e.g. the rate at which transmission lines ignite fires, the area burned by fires, or the concentration of property value in proximity to the lines).³ In other words, the risk reduction potential β does not provide information on how the retrofits reduce losses (e.g. by reducing ignition rates or by reducing the occurrence of very large fires). A more realistic treatment of the *Reduced loss* variable would use information from mechanistic models that explain how retrofits reduce ignition rates and fire sizes. However, this information is not in the public domain, since the Applications to Construct the tie line fire-hardening retrofits do not include quantitative estimates of the reduction in fire risk achieved by the projects.

Because the Monte Carlo simulation estimates the distribution of annual losses, we can simulate such losses for each year but need to convert them to present-value costs. This conversion allows the comparison between annual potential losses that could occur in any given year and the up-front cost of a long-lived retrofit project. The *risk weighted loss* is converted into a present value:

$$P.V. \text{ risk weighted loss}_i = \text{Risk weighted loss}_i * \frac{[1-(1+r)^{-n}]}{r} \quad (\text{eq. 8})$$

where: *P.V. risk weighted loss* = the present-value of risk-weighted losses over 30 years for line i ;
Risk weighted loss = Linear combination of expected value and standard deviation of annual loss for line i ;
 r = the discount rate; and
 n = the asset useful life, in years.

The base value of the discount rate is 8.4%, which is the regulated rate of return for SDG&E investments in their Application to Construct for the tie line 637 fire-hardening project (SDG&E, A.13-03-003). The base value of the asset useful life is 30 years, taken from the SDG&E Application to Construct for the tie line 6931 fire-hardening and wind interconnection project (SDG&E, A.12-12-007).

Finally, the net benefit is calculated by subtracting the retrofit costs and the reduced losses from the present-value risk-weighted losses before retrofits:

$$\text{Net Benefit}_i = P.V. \text{ risk weighted loss}_i - \text{Retrofit}_i - \text{Reduced loss}_i \quad (\text{eq. 9})$$

³ It is possible that, even after retrofits, a transmission line could ignite a fire that grows to a very large size and destroys significant amounts of property, because the destructiveness of the fire is ultimately driven by local patterns in weather, fuel loads, and settlement that are not affected by the retrofits. This analysis assumes that, once a fire starts, its eventual size and destructiveness are not influenced by the retrofit.

A positive net benefit means that the retrofit project lowers overall present value costs to the company. A negative net benefit means that the retrofit project increases overall present value costs to the company. The results of this analysis will be discussed in Section 6.2 below.

5.0 Data and Methods

The following sections describe the data sources and methods used to estimate the main elements of the Monte Carlo simulation, the random variables *Ignitions*, *Fire size*, *Location*, *Wildfire*, and *Windfire size*, which are combined with fixed parameters to yield the main model outputs.

5.1 Parameter Estimation

5.1.1 Ignitions

The random variable *Ignitions* represents the possibility of SDG&E equipment igniting a fire. It is modeled as a function of a fixed “spark rate” and the length of transmission line segment. This methodology was adapted from the testimony of Dr. Joseph Mitchell of the Murray Grade Road Alliance in testimony before the CPUC on fire issues related to transmission lines, and data from SDG&E disclosed as part of the Sunrise Powerlink transmission permitting and approval process was used to parameterize *Ignitions* (Mitchell).

The spark rate was estimated based on SDG&E records of all fires started by the company’s equipment. The dataset covers March 16, 2004 to October 22, 2007 (the date of the Rice and Guejito fire ignitions) and includes 121 separate events, mostly caused by the company’s distribution and secondary line systems ($n = 98$). 16 events were attributed to the transmission system, of which 9 were attributed to wind or to equipment failure. In some cases, the voltage of the lines could be determined by cross-referencing with SDG&E records of faults on their system covering the same time period. Finally, the total length of SDG&E’s transmission lines at various voltages was gathered from its Form 1 filings with the Federal Energy Regulatory Commission. These data were combined to estimate the rate at which SDG&E power lines ignite fires, based on the formula:

$$\text{Spark rate} = \frac{\text{Number of fires}}{\text{System length} \times \text{time period}} \quad (\text{eq. 9})$$

The following table shows the estimated rates at which SDG&E power lines ignite wildfires, measured as number of fires per year per circuit-mile of line. In general, the transmission system ignites fires at a lower rate than the distribution and secondary system, probably because transmission lines have taller utility poles and wider conductor spacing. Possible avenues for ignitions include contact with tree limbs, large birds touching multiple conductors, and wind blowing conductors into each other, all of which would presumably happen less frequently with taller poles and wider spacing (San Diego Gas & Electric Co., July 3, 2013). The table also contains the estimated rate of fire ignitions from wind or other equipment failures on the transmission system, as opposed to fires caused by other agents (birds, mylar balloons, vandalism, or vehicle crashes, for example). This distinction could have potential ramifications for the company’s liability: it seems doubtful that the company would be held liable for a fire resulting from a vehicle collision with a utility pole, whereas it would be liable for a fire resulting from a failure to maintain equipment in good working order. Finally, in seven cases the voltage of the transmission line could be determined by cross-referencing with recorded system faults. Ignition rates were calculated by voltage from these seven incidents, although these rates should be considered the minimum ignition rate because nine transmission system-caused fires could not be tied to specific voltage levels. The transmission system ignition rate of 0.00244 fires mi-1 yr-1 was used as the spark rate in the model for the seven transmission lines considered.

Table 3. Fires caused by SDG&E power lines, March 2003 - October 2007.

System	Fires	Years	Circuit miles	Spark rate (fires yr⁻¹ mi⁻¹)
Distribution & secondary	98	3.6	6759	0.00403
Transmission, all	16	3.6	1820	0.00244
Transmission - wind/failure	9	3.6	1820	0.00137
Transmission - 69 kV	3	3.6	886	0.00094
Transmission - 138 kV	1	3.6	269	0.00103
Transmission - 230 kV	3	3.6	387	0.00215

The possibility of an ignition on a given transmission line segment is a function of the spark rate and the length of each transmission line. The expected number of ignitions was estimated by:

$$E[Ignitions_i] = \text{Spark rate} * \text{Line length}_i \quad (\text{eq. 10})$$

The expected number of ignitions was assumed to equal the expected value of a Bernoulli variable with values of {0,1}. Thus, the expected number of ignitions represents the probability of an ignition on a given line. For the Monte Carlo simulation, $Ignitions = 1$ if $p < E[Ignitions]$, 0 if $p > E[Ignitions]$, where p represents a random draw. The table below contains the line length and $E[Ignitions]$ for each of the seven transmission line segments.

Table 4. Expected ignitions per year for each transmission line.

Line Segment	Length (miles)	E[I] (expected ignitions/yr)
TL 6931	5.2	0.013
TL 637	14.0	0.034
TL 6923	13.4	0.033
TL 682	20.2	0.049
TL 626	18.8	0.046
TL 625	22.5	0.055
TL 629	29.8	0.073

5.1.2 Fire size

Once a fire is ignited, the next major function of the model is to estimate the ultimate size to which the fire grows, the random variable *Fire size*, measured in acres. To determine the range of sizes, geospatial data from historical wildfires were examined to define a set of plausible wildfire events. Cal FIRE provides a geospatial dataset of historical wildfire perimeters across the state of California, stretching back to 1879. All fire events from 1950 to the present located partially or fully within the borders of San Diego County were extracted from this dataset. The resulting dataset is summarized in the table below. As the table makes clear, the distribution of wildfire sizes has an extreme right-hand tail. The variance of fire burned area is also very large, as reflected in the high coefficient of variation (ratio of standard deviation to mean). Since Cal FIRE includes information on the initial cause of wildfires, when known, the subset of fires caused by power lines was extracted from the dataset. We determined that three fires initially not included in the list of fires caused by power lines did in fact belong to that set, based on CPUC testimony and Cal Fire summary statistics: the Laguna fire (1970), Witch fire (2007), and Rice fire (2007).

From the table and figure below, it is clear that fires caused by power lines tend to be much larger in size than average fires. One possible explanation for this finding is the contribution of high winds to both power line failures and to large fires. High winds can lead to power line failures that cause fires, as seen in the Witch, Rice, and Guejito fire ignitions. Fires that start in high wind conditions are harder to control. For example, attempts to control the Witch Fire by

dropping water from an air tanker were thwarted by high winds (Cal Fire et al, 2008). The high winds also contributed to the rapid spread of the fire through spotting, or small fires started by wind-borne embers carried up to ½ mile ahead of the main fire (Cal Fire et al, 2008).

Table 5. Fire size distributions for all fires and for power line-related fires.

	All fires	Power line fires
Count	984	12
Sum (acres)	2,130,802	426,957
Mean (acres)	2,165	35,580
Std. Dev. (acres)	12,939	61,659
Minimum (acres)	0	20
1st Quartile (acres)	60	152
Median (acres)	157	585
3rd Quartile (acres)	650	28,788
Maximum (acres)	270,685	174,161

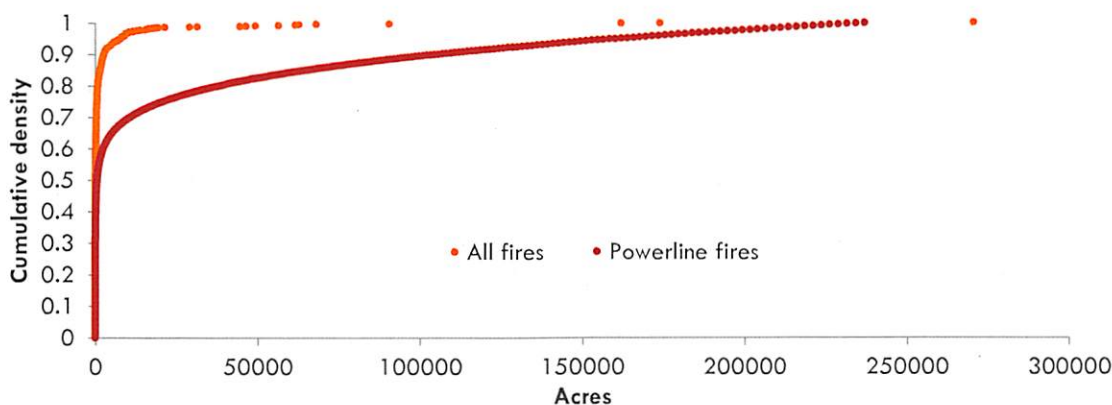


Figure 2. CDF of fire size for all fires is derived from empirical data. CDF of fire size for power line fires is approximated by a cubic regression of the empirical CDF on log-10 fire size.

The fire burned area data from Cal Fire was used to create a probability distribution of fire sizes. The fires were ranked in ascending order to calculate the cumulative probability of a fire reaching a certain size in acres and produce the cumulative density function (CDF) shown in Figure 2. This process was repeated for fires caused by power lines, although the small number of such fires ($n = 12$) means that drawing from the empirical distribution for the Monte Carlo simulation would result in dozens of iterations returning the exact same burned area. To increase the potential variation in burned area, continuous probability distributions were fit to the empirical data to allow for the prediction of values between and outside of the observed values. For all fires, a gamma distribution with shape parameter (k) of 8.8 and scale parameter (Θ) of 0.3 offered a good approximation of the log-base 10 transformed fire size distribution. For the power line fires, a cubic regression of empirical CDF on log-base 10 transformed fire size gave a good approximation of the CDF, with the form: $CDF = 0.0141 \cdot \text{size}^3 - 0.148 \cdot \text{size}^2 + 0.670 \cdot \text{size} - 0.521$, truncated to include only values between 0 and 1. The distributions are shown in the figure above.

5.1.3 Location

The location at which a fire starts influences the quantity and value of property it eventually damages. Fires ignited in close proximity to dense human settlement have the potential to cause much more property damage than fires ignited in sparsely populated wildlands. To model the influence of geospatial location on fire destructiveness, a *Location* random variable was added to the Monte Carlo simulation model. First, potential ignition points were modeled along the transmission line routes at 0.5 kilometer spacing using ArcGIS. Next, the assessed improved value of each property (i.e. the value of the structure, separate from the land value) within 20 kilometers of the transmission lines was obtained from San Diego County GIS Services. For each property, the assessed improved value was then weighted by the wildfire threat index, as measured by Cal Fire, to create a potential damage value. This weighting process was used to avoid inflating damage estimates by including structures in very low risk areas, such as urban areas, that would be unlikely to burn in the event of a wildfire. Cal Fire's assessed fire threat is based on the fire return interval (less than 100 years for most of the study area) and the flammability of the fuels. The weights used were: Little or no threat, 0.0; Moderate, 0.25; High, 0.5; Very high, 0.75; and Extreme, 1.0. The Cal Fire methodology for assessing fire threat is intended for state-wide application, not for the estimation of the potential for damage at a specific location, so the calculated potential damages should be considered rough estimates. Finally, the potential damage values within radii of 0 to 20 kilometers to the ignition points, corresponding to fire sizes of 0 to 300,000 acres, were summed. The resulting table contained the potential damage for a fire size of 0 to 300,000 acres for each of the 390 potential ignition points.

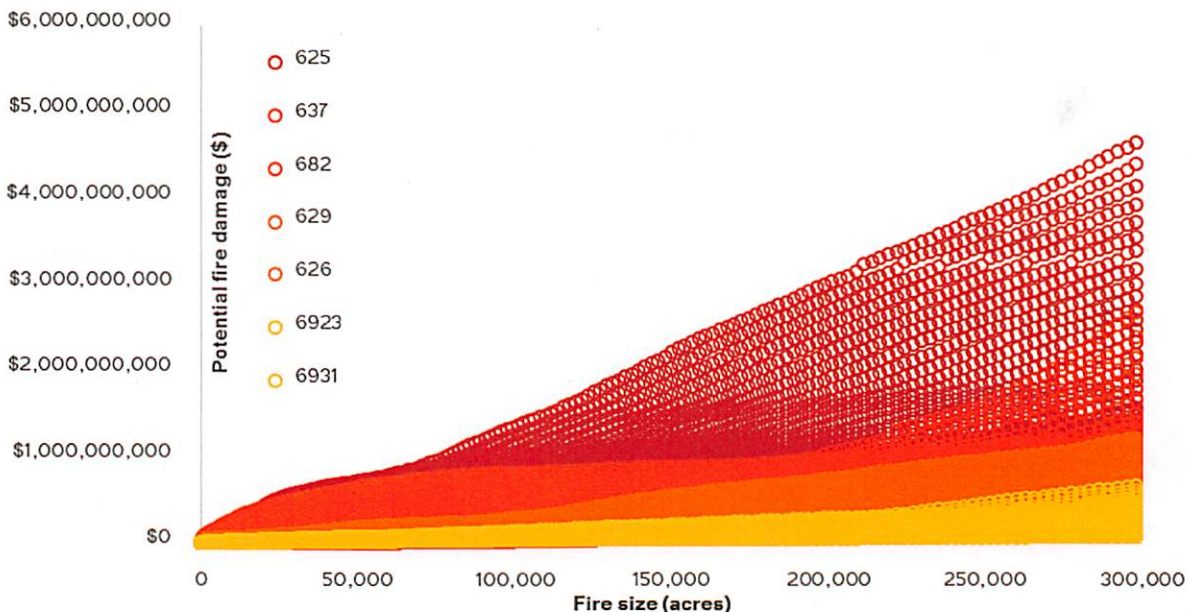


Figure 3. Potential property damage from fires ignited by transmission lines. Potential damages consist of the sum of building values within certain radii of ignition points along transmission lines. Building values are weighted by the fire threat assessed by Cal Fire for each building location.

The figure above shows the potential damage values for each ignition point, grouped by transmission line. The maximum potential damage from a very large fire is much higher for some lines (625, 637, 682) than others (6923, 6931). For example, the maximum potential damage for a fire ignited on line 625 is \$4.9 billion, while the maximum potential damage for a fire ignited

by line 6931 is only \$97 million. The western termini of lines 625 and 637 are located in densely-settled areas, the communities of Lakeside, Alpine, and Ramona, which explains the high potential for damage from fires ignited in those areas. However, even those lines pass through areas with much lower concentrations of property value where a fire might do much less damage. The minimum potential damage for a 300,000 acre fire on lines 637 and 625 is \$716 million and \$840 million, respectively – much lower than the potential for damage from a fire ignited on the western ends of the lines. For a 300,000 acre fire, total potential damages range from \$250 per acre to \$15,600 per acre. The total estimated liability for SDG&E for the 2007 fires (approximately \$11,600 per acre) lies near high end of this range, as do the per-acre insured loss estimates for three other major southern California fires, the Witch, Cedar, and Old fires (Insurance Information Institute, Inc, 2014).

The random variable *Location* allows the model to take into account variability in potential damages by location of ignition. We assume that every point on a transmission line is equally likely to ignite a fire, and hence assign to each point a probability of being the location of ignition:

$$\text{Prob. of marker } k \text{ being ignition point on line } i = \frac{1}{\text{Total number of markers}_i} \quad (\text{eq. 11})$$

For each fire event (*Ignition* = 1), a random draw of *Location* is evaluated to determine the ignition point at which the fire starts. The potential damage table then provides the damage caused by that fire by indexing the ignition point and the expression of the *Fire Size* random variable.

5.1.4 Wildfire

The random variable *Wildfire* represents the incidence of naturally-occurring wildfires that damage transmission lines in a given year. It is modeled as a function of the annualized probability of a wildfire for each transmission line, based on the wildfire return interval (i.e. the average number of years between fires) for that line. The wildfire return interval for each section of line was estimated from historical observations using the Cal Fire wildfire perimeter dataset. The number of fires observed along the location of each segment of line was counted for the time period of 1950 - 2012. The length of line with different fire frequencies are shown in the figure below. Based on the historical record, certain lines (626 and 637) experience fires at a higher rate than others (6931, 629). It should be noted that this analysis is based solely on geospatial overlays of historical fire perimeters and the transmission line locations. The extent of damage to structures within the fire perimeters is not known. In other words, a transmission line could be within the perimeter of a historical fire but could escape damage.

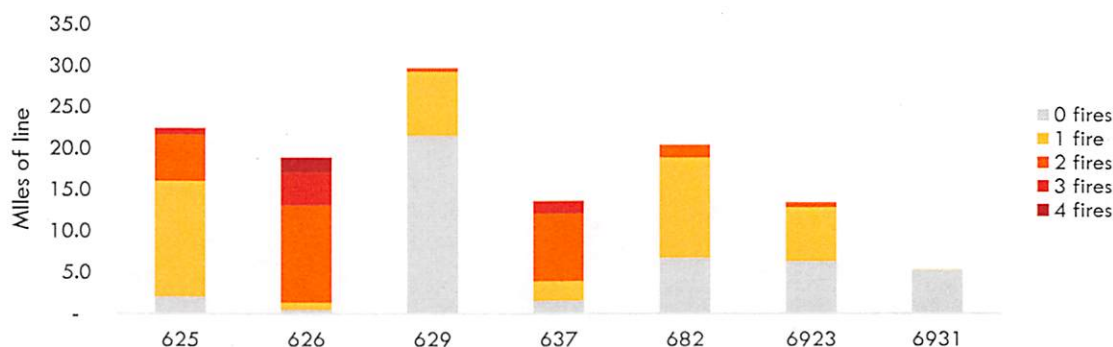


Figure 4. Fire frequency by length of transmission line, 1950 – 2012.

The historical incidence of fires along the transmission line routes was converted into a single annual probability of a wildfire occurring on the line. The probability of a wildfire is given by:

$$Wildfire_i = \sum_{j=0}^4 \left[\frac{Fires_j}{Years} * Length_j \right] / Total\ Length \quad (eq. 12)$$

where: *Wildfire* = the annual probability of a wildfire on line *i*;
Fires = the number of historic wildfires on segment *j* of line *i*;
Length = the length of segment *j*;
Years = the time period, in this case 62 years; and
Total length = the total length of line *i*.

The annualized probability of a wildfire for the entire line thus reflects the average number of fires experienced by the line over the time period (the basis of the fire return interval), weighted by length of line. For segments of line where no fires were observed over the time period, an annual fire probability of 1% was assumed, corresponding to a fire return interval of 100 years.

For each line, the occurrence of a wildfire is assumed to follow a Bernoulli distribution {0,1} with a probability equal to (1 - *Wildfire*). If a random draw from *Wildfire* exceeds this fire probability, a wildfire is assumed to affect that line. The table below shows the annual probability of wildfire for each of the line segments.

Table 6. Historic wildfires along transmission line routes, and estimated annual probability of wildfire for those lines.

Line	Length (miles)	Length, 0 fires	Length, 1 fire	Length, 2 fires	Length, 3 fires	Length, 4 fires	Weighted # of fires	Annual probability
625	22.4	2.0	14.0	5.7	0.7	-	1.23	2.07%
626	18.8	0.4	0.9	11.8	4.0	1.7	2.30	3.73%
629	29.7	21.5	7.8	0.4	-	-	0.29	1.19%
637	13.6	1.5	2.4	8.2	1.5	-	1.72	2.88%
682	20.4	6.6	12.2	1.6	-	-	0.75	1.54%
6923	13.4	6.2	6.5	0.6	-	-	0.58	1.40%
6931	5.2	5.2	0.1	-	-	-	0.01	1.01%

5.1.5 Wildfire size

The random variable *Wildfire size* represents the length of line affected by potential wildfires. It is modeled as a uniform random variable, with values drawn from empirical observations of the length of line that affected by historical fires. To develop this random variable, the individual perimeters of all fires that intersected the transmission lines were extracted from the Cal Fire dataset in ArcGIS. The transmission line routes experiences between 1 (TL 6931) and 12 (TL 625) separate fires over the time period of 1950 to 2012. Next, the length of line affected by each individual fire was calculated. Most fires affected only a small portion of the line routes (10% or less), although the most destructive fires affected 50% or more of the line length. Finally, each fire was ranked in ascending order of line affected to create a cumulative density function for the amount of line affected by each individual fire. The results are shown in the figure below.

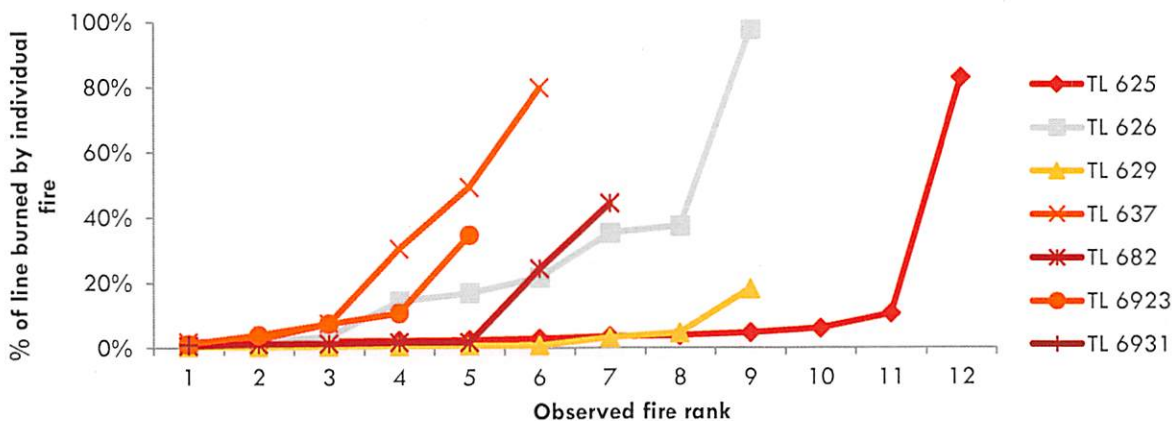


Figure 5. Portion of total line length affected by individual historical wildfire events.

The *Wildfire size* random variable draws from the empirical cumulative density function of wildfire size displayed above. *Wildfire size* is modeled as a uniform random variable such that, for each line, each level of observed fire damage is equally likely. Although this approach reflects the historical occurrence of fires on line routes, it does not capture the potential for future fires to damage greater portions of line than have past fires. For example, the model limits the maximum amount of damage sustained by line 6931 to 1% of the total length, reflecting the low incidence of wildfires in the past (i.e. the only fire to have affected that line route burned 1% of the total route). In reality, local fuel and weather conditions could lead to fires on that route burning much greater sections of line.

The company's repair costs are estimated by multiplying the miles of transmission line damaged by wildfires by the repair rate. A flat repair rate of \$1.92 million per mile was used as a base. This value comes from SDG&E's cost estimates for new 69 kV single-circuit transmission lines, published with CAISO. This value should be viewed as a worst-case scenario for repair costs. By comparison, after the 2003 Cedar Fire SDG&E repaired 45 miles of line at a cost of \$7 million, while after the 2007 firestorm the company repaired 56 miles at a cost of \$16 million (San Diego Gas & Electric Company, 2012). Those repairs cost approximately \$150,000 to \$300,000 per mile, much less than the cost of constructing new line as modeled in the Monte Carlo simulation.

6.0 Results

6.1 Monte Carlo Simulation Results

The Monte Carlo simulation was run with 10,000 iterations to estimate the range of potential losses that could result from fires, both system-wide and for each individual line. Total losses, including liability and repair costs, were calculated for each iteration. Liability was also calculated a second time for each iteration using the Fire Size distribution drawn from historical fires caused by powerlines; these results are denoted Liability – Extreme in the following discussion. Average Liability, Liability-Extreme, Repair costs, and Losses were calculated from the 10,000 iteration results, as was the standard deviation in those outputs.

The following figure shows a histogram of liability and liability-extreme results over the 10,000 simulation iterations. Iterations with liability or liability-extreme of \$1M or less are not shown on the diagram, but the vast majority of iterations had costs in this range: 92% of runs had liability less than \$1M, and 86% of runs had liability-extreme of less than \$1M. The histogram shows a

very long right-hand tail of extremely costly events with very low probabilities of occurring (e.g. only 10 iterations out of 10,000 had liability-extreme of \$1B or more).



Figure 6. Histogram of liability and liability-extreme over 10,000 iteration runs. Results lower than \$1M were excluded for display purposes. 86% of runs had liability-extreme less than \$1M; 92% of runs had liability less than \$1M. Labels indicate the count of liability-extreme results in each range.

One useful tool for risk analysis is the exceedance probability curve, which shows the reciprocal of the cumulative probability distribution function (i.e. $1 - \text{CDF}$) of losses (Grossi & Kunreither, Catastrophe Modeling: A New Approach to Managing Risk, 2005). Such exceedance probability curves portraying the annual probability of exceeding certain levels of liability-extreme, based on the results of the Monte Carlo simulation, are shown below. The results suggest an 80% chance of zero liability in a year, a 1% chance of liability greater than \$500M, a 0.1% chance of liability greater than \$1B, and a 0.02% chance of liability greater than \$1.5B in a year. In other words, the most damaging, worst-case fire events have a very low probability of occurrence.

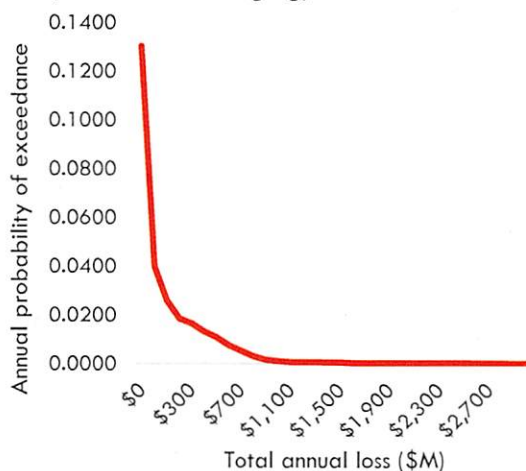


Figure 7. Exceedance probability curve for total liability-extreme in a year.

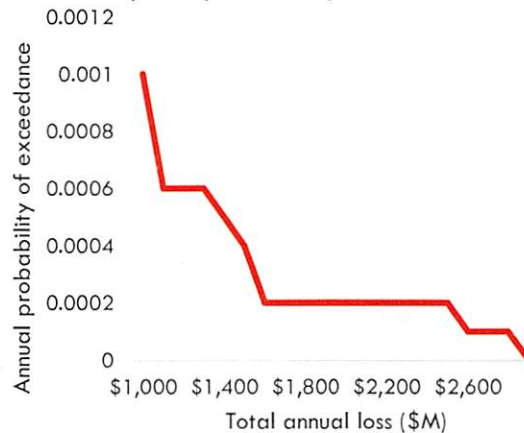


Figure 8. Exceedance probability curve for total liability-extreme in a year, focused on events greater than \$1B

The table below shows the annual liability, liability-extreme, repair cost, and losses. In this case, losses were calculated by summing the liability-extreme and repair cost for a given iteration. From the table, it is clear that average liability and repair costs are dwarfed by the average liability-extreme costs. Average liability and repair are relatively minor (\$2.5 M / year) given the scale of the proposed retrofit investments and SDG&E's annual income. The liability-extreme costs are much higher than liability or repair costs, reflecting the fact that the fire size distribution

of powerline-related fires leads to much greater fire sizes and subsequent property damage. The other major finding from the table is the extreme variability in the results: the average values are dwarfed by the standard deviation (high coefficients of variation). This finding further highlights the role that very low probability, high-cost events have in driving potential losses.

Table 7. Average costs (liability, liability-extreme, repair, and losses) and standard deviation of costs.

	Liability	Liability - Extreme	Repair	Losses
Mean (\$M)	1.7	19.1	0.8	19.9
Std. Dev. (\$M)	20.1	106.3	3.7	106.5
Maximum (\$M)	807.7	2,975.0	43.7	2,975

Losses were calculated for each transmission line in addition to system-wide losses. The figures below show the average losses, standard deviation of losses, and maximum losses for each tie line. Losses were calculated by summing liability-extreme and repair costs. The results show considerable variability: the standard deviations in losses are much greater than the average losses and are in turn dwarfed by the maximum observed losses. All three measures vary greatly by transmission line, with the greatest losses arising from lines 625 and 637. The losses on other lines, especially 6931 and 6923, are relatively small, reflecting the low concentration of property value in proximity to these lines.

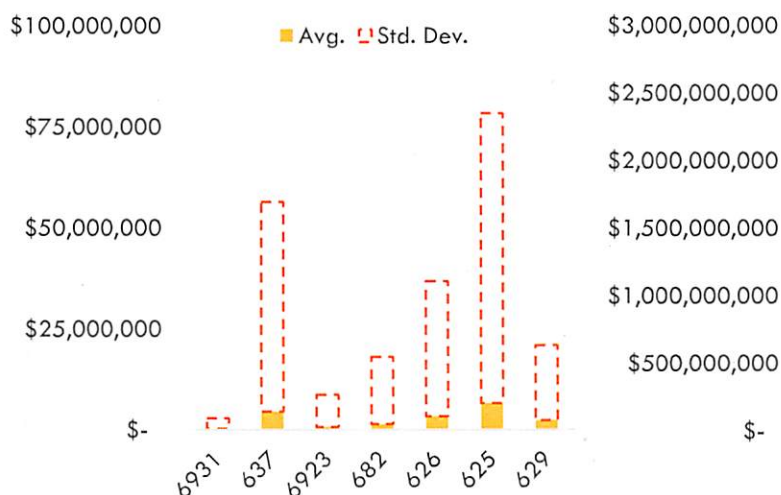


Figure 9. Average losses per line and standard deviation of losses per line. Losses are the sum of liability-extreme and repair costs.

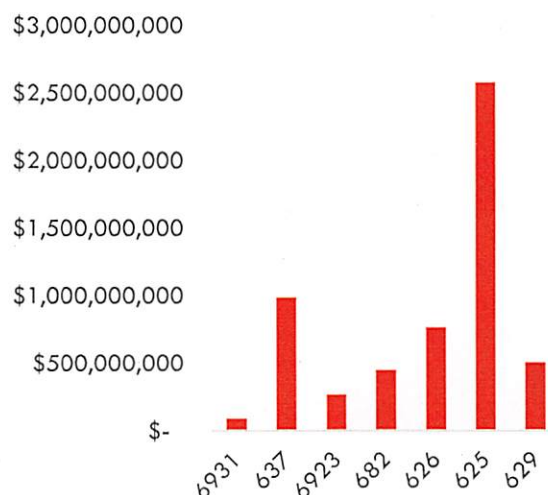


Figure 10. Maximum losses per line resulting from the Monte Carlo simulation. Losses are the sum of liability-extreme and repair costs.

The remainder of this analysis will focus only on total losses produced by the liability-extreme results, since these losses are generally large enough to warrant further analysis of retrofit cost-effectiveness.

6.2 Fire Cost Minimization Curve Results

The annual losses and variability in losses for each line segment were used to evaluate the cost-effectiveness of the retrofit projects using the fire cost minimization curve framework. First, annual expected losses were converted into present value risk-weighted losses using equations 5 and 6. For the initial analysis presented below, a risk premium of 10% was used to weight the variability in potential losses ($\alpha = 0.1$). Next, the retrofits were assumed to reduce the present value of risk-weighted losses by 75% ($\beta = 0.75$). The resulting reduced losses were then added to the costs of

each retrofit project. The difference between the risk-weighted loss and the sum of reduced loss and retrofit cost is the net benefit of the project.

The figure below shows the net benefit of the retrofit projects with a risk premium of 10% and retrofit effectiveness of 75%. Given these assumptions, retrofitting lines 625 and 637 has a positive net benefit. For the other lines, the retrofit costs exceed the expected losses, so retrofitting has a negative net benefit. For example, the costs of retrofitting line 629 are approximately 3 times larger than the present value of all potential losses on that line over 30 years, so the retrofit has a negative net benefit of more than \$100 million.

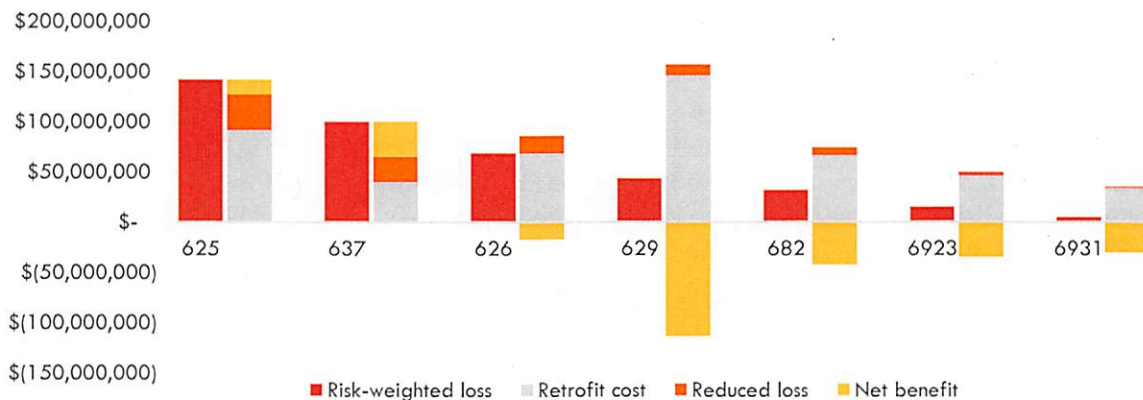


Figure 11. Net benefit of retrofit projects. Loss w/o retrofits represents the present value of risk-weighted loss with $\alpha = 0.1$. Loss w/ retrofit represents the reduced loss with $\beta = 0.75$. The net benefit is the change in present value associated with building the retrofit.

The components of the net benefit analysis are added on a cumulative basis to create the fire cost minimization curve, shown in the figure below.

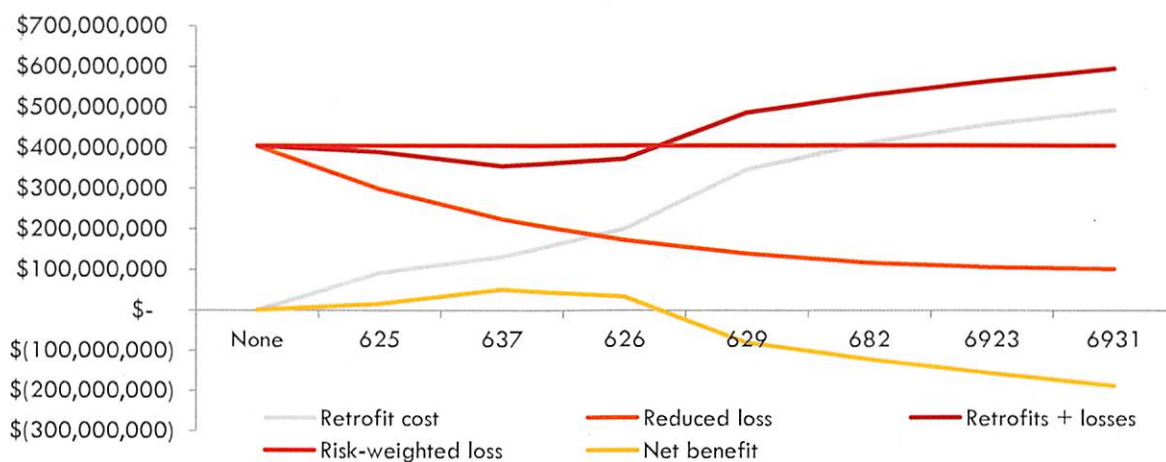


Figure 12. Fire cost minimization curve. The optimal level of fire protection is the minimum of the sum of retrofit costs and reduced losses (retrofits + losses, dark red). Under these assumptions ($\alpha = 0.1$, $\beta = 0.75$), the optimal level of protection is to retrofit lines 625 and 637; any further retrofit projects increase total costs.

The figure shows how system-wide costs ("Retrofits + losses") decline with the first two retrofit projects on lines 625 and 637, but then begin to rise with each subsequent project. The cost-minimizing level of protection (or the maximum net benefit) occurs with the retrofit of these two

lines only. For transmission lines 629 and beyond, retrofits actually increase total system costs beyond the base level of risk-weighted losses with no retrofits. In other words, the retrofits are more costly than the risk-adjusted expectation of losses from fires themselves.

Assumptions about the effectiveness of fire-hardening retrofits and the risk premium of decision-makers are extremely influential in determining the cost-effectiveness of various fire-hardening projects. Assuming that retrofits reduce losses by 100% makes those retrofits more valuable than if they are assumed to reduce losses by only 50%. Similarly, assuming a higher risk premium will generally make the retrofits more attractive investments, since the average potential loss is much smaller than the variability in potential losses. The following figure shows the positive net benefit frontiers for each of the transmission lines. These frontiers show the minimum combinations of retrofit effectiveness and risk premium that are required to achieve a positive net benefit. For example, at a 50% effectiveness and 50% risk premium, lines 637, 625, and 626 have positive net benefits.

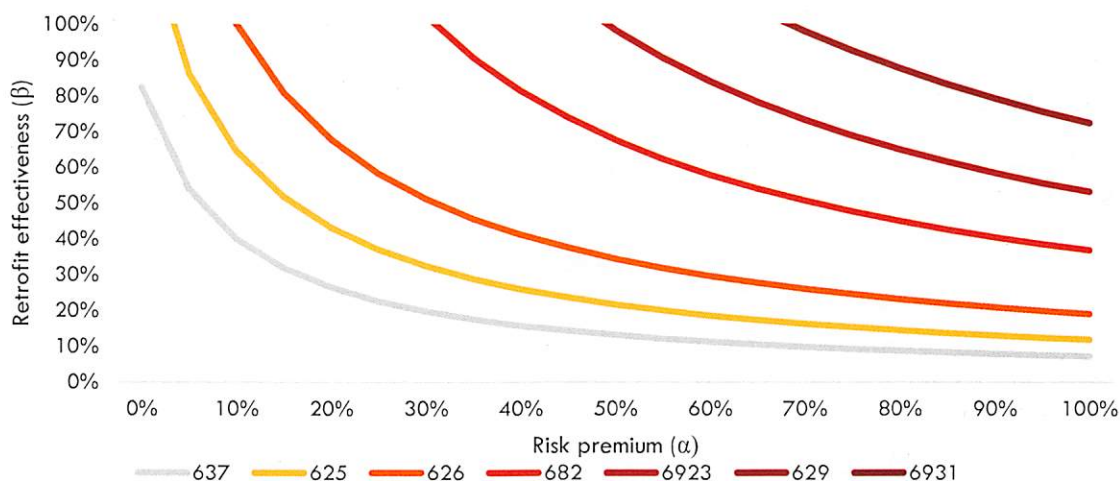


Figure 13. Positive net benefit frontiers for each transmission line. Each curve represents combinations of effectiveness and risk premium assumptions for which the retrofit has a net benefit of zero. The retrofit has a positive net benefit for all points above the curve. Line 6931 does not have a positive net benefit for any combination of risk premium and effectiveness.

7.0 Conclusions

This section summarizes the key findings of the analysis, describes potential refinements to the model and analytical approach, and suggests implications of the results for policymakers at the company and elsewhere.

7.1 Model findings

Five key insights from the analysis are discussed below.

1. **Wildfire risks are spatially dependent.** The geospatial analysis undertaken as part of this study showed clear spatial patterns in the distribution of both fire history and property values. In general, the greatest fire frequency is found in the Cuyamaca Mountains and Cleveland National Forest in the central portion of the County, with additional high-frequency pockets in the northwest on Camp Pendleton and southwest near Jamul. The transmission lines in these areas, notably 625, 626, and 637, experience frequent wildfires over most of their routes. The remaining lines in the study experience wildfire less frequently and only along isolated sections of their routes. The distribution of risk-

weighted property value also follow broad patterns, with the greatest concentrations of potential damage located in the communities to the west of Cleveland National Forest such as Alpine, Ramona, and Lakeside. The lines in closest proximity to those communities, especially 625 and 637, create a much greater exposure to liability than lines near less populated areas.

2. **Risk exposure is driven by extreme events.** The distribution of annual losses generated by the Monte Carlo simulation has a very long right-hand tail of very low probability, very high impact events. For 80% of the model iterations, total losses were zero, implying no ignitions, no land burned, and no wildfires that damage lines. In iterations in which fires cause losses for the company, losses are generally minor compared to the company's annual revenues or to its liability for the 2007 fires. Only in a small number of cases (0.1%) do total losses exceed \$1 billion. The discussion of the cost-effectiveness of the retrofit projects should reflect the importance of these low-probability, high-loss events.
3. **Liability exposure dwarfs repair costs.** Liability costs, not repair costs, were the main drivers of total losses. The maximum system-wide liability in a single year observed over 10,000 simulation runs was \$2.97 billion, whereas the maximum system-wide repair cost in a single year was \$44 million. Similarly, the expected value of liability costs was \$19.2 million, versus an expected value of repair costs \$0.79 million, over the 10,000 iterations. This result broadly reflects the financial impact to SDG&E of the 2007 fires, in which liability (an estimated \$2.4 billion to settle all claims) dwarfed the costs of repairing lines (\$16 million to repair 56 miles of line) by orders of magnitude. Although the costs of repairing fire-damaged lines are mentioned in Applications to Construct as justifications for retrofits, the results of this analysis indicate that expected repair costs alone are not sufficient grounds for retrofitting the lines.
4. **The fire size distribution matters.** As discussed in Section 5.1.2, fires ignited by power lines appear to burn larger areas than fires ignited by other causes. The analysis investigated this dynamic by comparing liability generated from draws from the "all fires" size distribution with liability-extreme generated from draws from the "power line fires" size distribution. In general, the losses resulting from the "all fires" distribution are not large enough to justify retrofits: the expected annual value of losses is only \$1.7 million, with a standard deviation of \$20 million and maximum observed loss of \$808 million. Retrofits can be justified under certain risk tolerance and effectiveness assumptions if we expect the fires ignited by the transmission lines to follow the power line fire size distribution, i.e. to attain much greater sizes. This finding could provide justification for retrofits that address wind-related line failures (i.e. heavier conductors, wider conductor spacing, etc.) due to the nexus between wind speeds, line failures, and large fires.
5. **Risk tolerance and effectiveness assumptions determine net benefits.** The net benefit of retrofitting a given line depends on assumptions about risk tolerance and retrofit effectiveness. For a risk-neutral investor (i.e. risk premium $\alpha = 0$), only the retrofit of line 637 could be justified, and only then under assuming that the retrofit reduces losses by 80% or more. As the risk premium and assumed effectiveness increase, more retrofit projects have a positive net benefit. If the actual risk premium used by SDG&E decision-makers were known, or the actual effectiveness of the retrofits in reducing losses, this framework could be used to determine which retrofits have positive net benefits. Even without these values, however, the analysis provides a framework for prioritizing retrofit projects from most to least cost effective, with the most effective projects requiring the lowest risk premiums and effectiveness assumptions to be justified.

7.2 Potential refinements

This study examined the risk of wildfires using a probabilistic approach based largely on past fires. The decision to use this probabilistic approach was driven largely by the availability of data in the public domain with which to conduct the analysis. With additional time and data, the analysis could be expanded and refined to more accurately model the dynamics at play. Three potential refinements are discussed below.

1. **Multi-year time horizon.** The Monte Carlo Simulation is formulated to provide the wildfire-related losses in a single year, so the probability distributions of the random variables are the same for each model iteration. This formulation does not capture the change in fire risk over time. For example, the growth of chaparral vegetation might increase the probability of a fire over time as fuel loads build up on the landscape. Explicitly modeling a multi-year period could capture this dynamic. Similarly, the probability of future fires is conditional on past events due to changes in fuel loads and vegetative cover following a fire. If a fire burns all available fuels, fire risk would be reduced below the pre-event baseline for several subsequent years while vegetation regrows. Conversely, if a fire leads to the replacement of native chaparral vegetation with invasive grasses, the fire risk for that area could be elevated above the pre-event baseline for future years. In addition, human settlement of the wildland-urban interface is expected to continue in the future, which will change the concentrations of property values in proximity to the transmission lines. Expanding the analysis to explicitly model a multi-year time horizon that extends through and beyond the useful life of the retrofits could allow for better representation of these changing risks and their impact on potential losses over the project life. A multi-year analysis could also provide a framework for examining the potential impacts of climate change on fire risk.
2. **Geophysical fire spread models.** The model does not consider local terrain or vegetation when evaluating the area burned by a fire ignited by power lines. Instead, the fire is represented as a circle centered on a marker point along the transmission line, and the amount of area burned is determined by a draw from the fire size distribution. In reality, the local terrain and fuel conditions at each potential ignition point would influence how large a fire grows and what specific locations it burns. For example, the Witch Fire burned westward and southward from its initial ignition point due to winds, topography (it burned downslope and down canyons), and fuel availability (Cal Fire After Action). A fire spread model could consider terrain and vegetation cover in determining where a fire is likely to burn after initial ignition, how large a size it is likely to attain, and which properties it is likely to threaten. Incorporating such a model into the analysis would provide a more detailed and realistic estimation of the potential liability for fires ignited along different portions of the transmission lines. It might also reveal particular segments of the line with very high fire risk that would benefit from targeted mitigation actions, such as vegetation management, that reduce risk without requiring retrofits.
3. **Additional fire costs.** This study only considered damage to property in evaluating the potential financial losses from fires ignited by transmission lines. SDG&E's public 10-K filings do not disclose the extent to which non-property costs contribute to the company's overall liability and legal defense costs related to the 2007 fires, so these costs were not included in the model. In reality, the social costs of wildfires include many more components beyond structure damage. Possible costs that could be included in the analysis include firefighting expenses, liability for human injuries or deaths, evacuation and disaster response costs, lost economic output, costs of electrical service disruption, costs of ecological damage, and fines and penalties. Adding estimates of these costs to the model

would provide a more realistic estimate of the social costs of fires beyond the liability faced by the company. Potential ecological damages from wildfire (e.g. sedimentation in burned watersheds, replacement of native vegetation with invasive species, loss of critical habitat, etc.) in particular could be added to geospatial fire spread modeling to improve understanding of the spatial variability in fire costs. Adding these costs to the model would allow decision-makers to consider costs borne by society, not the company, which might influence the evaluation of the retrofits' benefit to ratepayers.

7.3 Policy implications

The confluence of fire-prone chaparral vegetation, widespread settlement in the wildland-urban interface, and intense Santa Ana winds creates a significant wildfire hazard in San Diego County. For this reason alone, wildfire risks should have particular salience for managers at SDG&E. The company's experiences in the aftermath of the 2007 fires, including major legal costs, scrutiny by regulators, and negative publicity, have spurred SDG&E to make wildfire risk mitigation a major priority of the company (San Diego Gas & Electric Co., July 3, 2013). The 2007 fires also spurred the CPUC to initiate a major rulemaking to examine and revise its safety regulations related to wildfires, Order Instituting Rulemaking I.08-11-005. Both regulator and regulated entity clearly have an interest in reducing wildfire risk for the benefit of the public and the company.

Quantification of wildfire risks and the risk reduction potential of mitigation projects could help both regulators and SDG&E evaluate protection options. As this study has shown, different transmission lines contribute differently to the company's overall risk exposure. Decision-makers therefore need information on those risks in order to prioritize between different fire-hardening projects and between fire-hardening and other fire mitigation options. From the regulator's perspective, requiring risk quantification data and analysis in applications for project approval could help ensure that investments in fire-hardening are cost-effective in reducing fire risk. From the company's perspective, quantification could help target investments at the elements of its infrastructure with the greatest risk of fire.

A related issue is the need for discussion about the level of residual risk acceptable to the company, the regulator, and the public. This analysis shows how the net benefit of retrofits is sensitive to the risk premium used to estimate the utility function for losses. However, different decision-makers might weight risks differently (for example, by placing greater weight on the maximum possible loss or a different moment from the loss distribution). Because of these different risk weightings, different parties could look at the same set of mitigation projects and arrive at divergent conclusions on the projects' benefits. The discussion of project benefits in a regulatory context could benefit from dialogue on the different risk tolerances of the public and company.

Finally, policymakers should consider the social equity implications of fire protection projects. Utilities have an obligation to serve customers in high-hazard areas, which exposes their infrastructure to hazards, but the costs of mitigating those risks or restoring service post-disaster are generally borne by the utilities' broader customer base. An alternative approach might include efforts to apportion the costs of fire protection to the customers whose choice to live in high fire threat areas drives the company's risk exposure. This approach might take the form of a fire risk surcharge added to monthly bills for rural customers. Rather than spreading the costs of fire risk (both protection measures and realized losses) across all customers in the service territory, including those living in low-hazard areas, this approach would push those costs onto customers whose choice to live in high-hazard areas contributes most to those risks.

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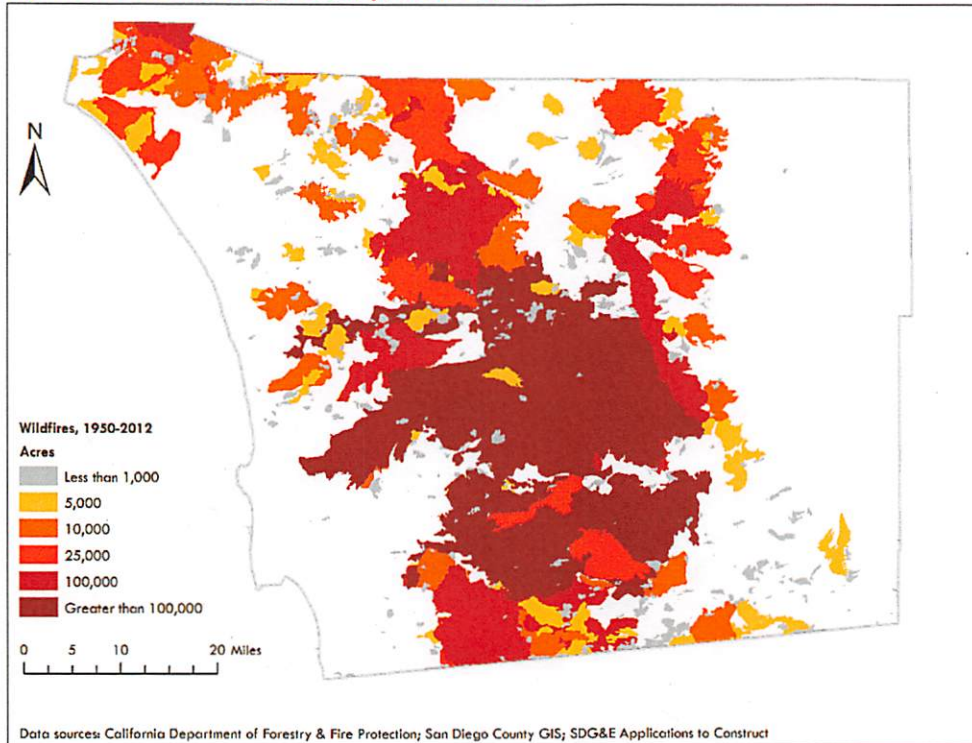
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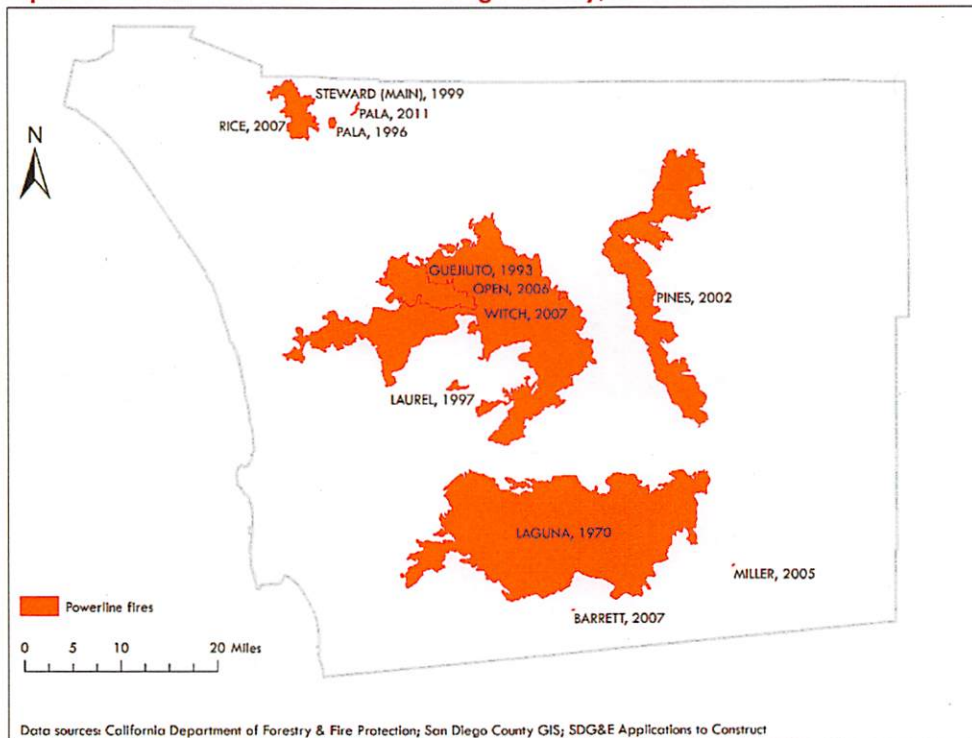
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10.0 Appendix

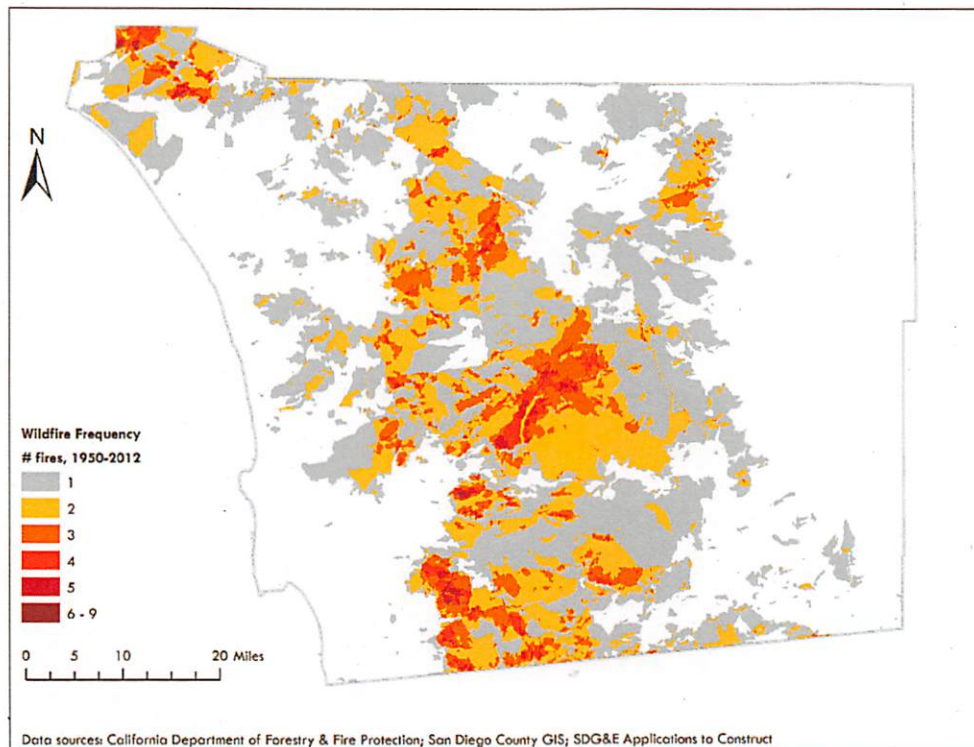
Map 1: Fires in San Diego County, 1950 - 2012



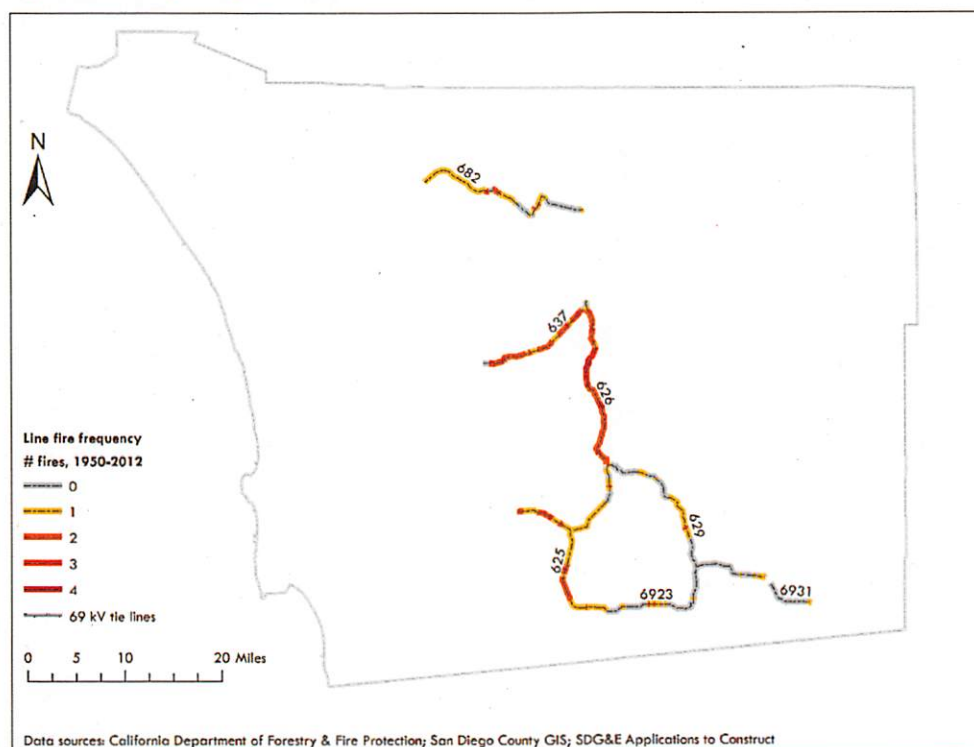
Map 2: Power line related fires in San Diego County, 1950 - 2012



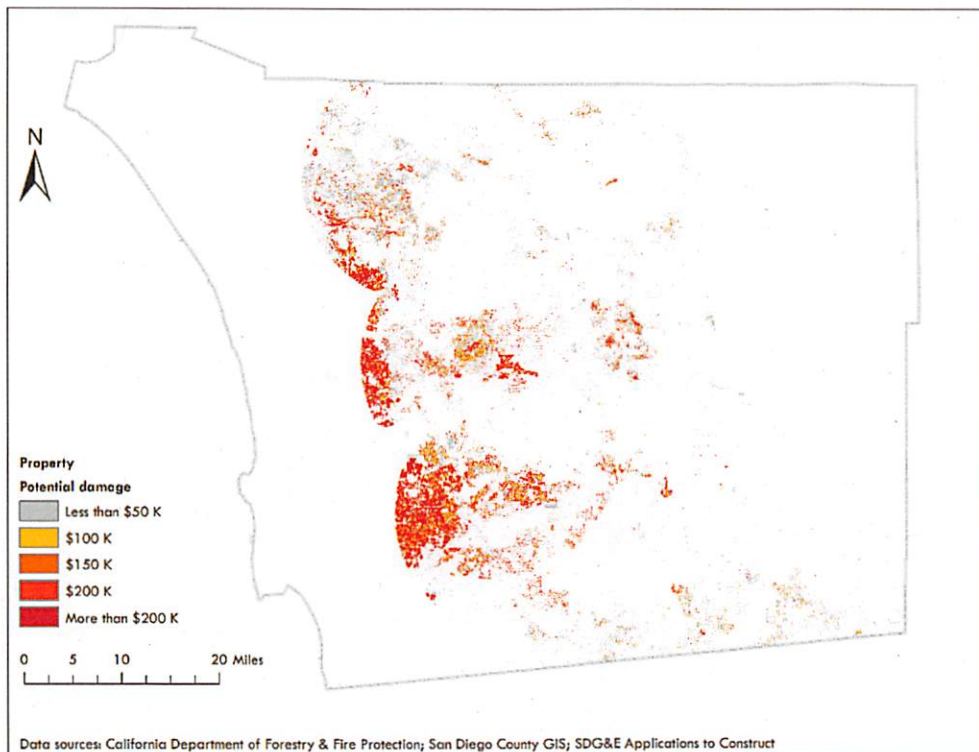
Map 3: Fire frequency in San Diego County



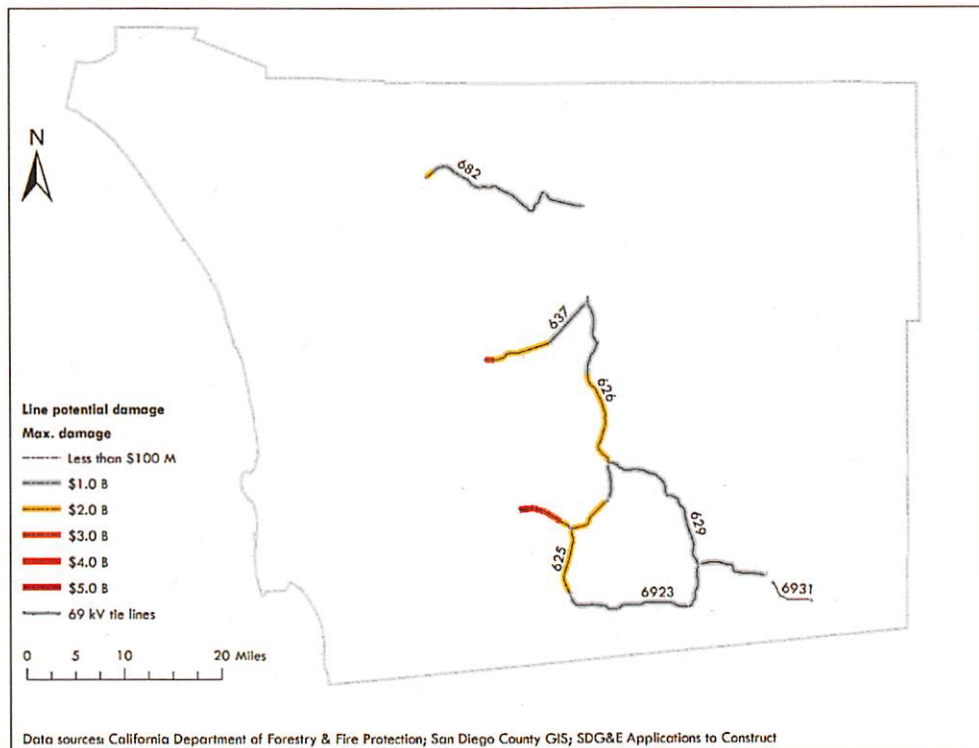
Map 4: Fire frequency on 69-kV transmission lines



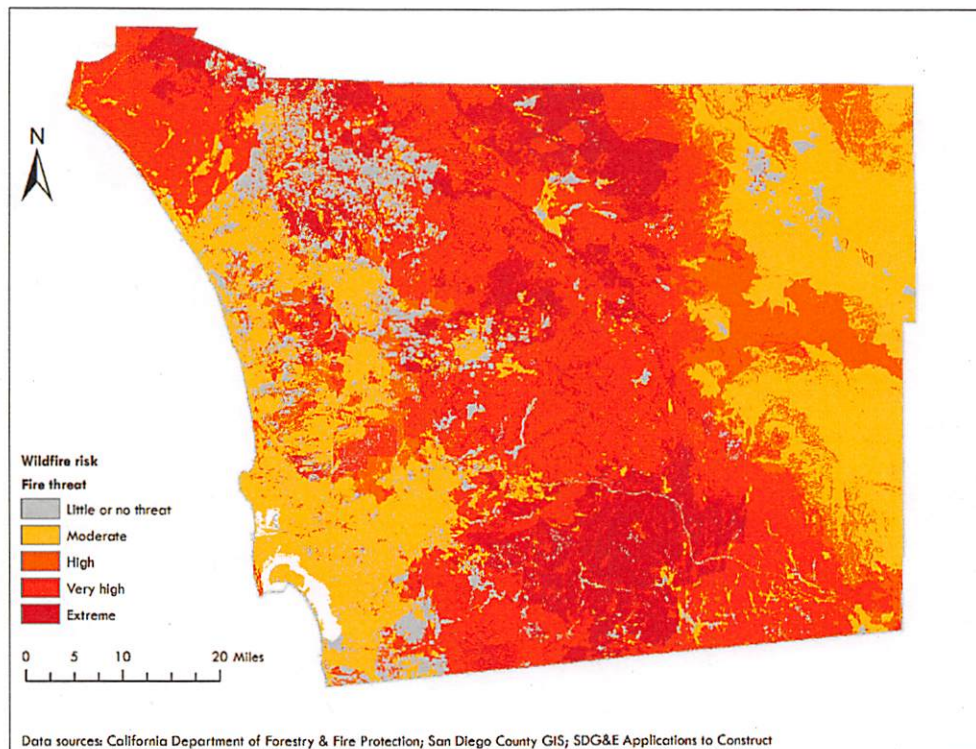
Map 5: Potential property damage within 20 km of fire-hardening transmission lines



Map 6: Maximum potential damage for fires ignited by 69-kV transmission lines



Map 7: Fire threat assessed by Cal Fire



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